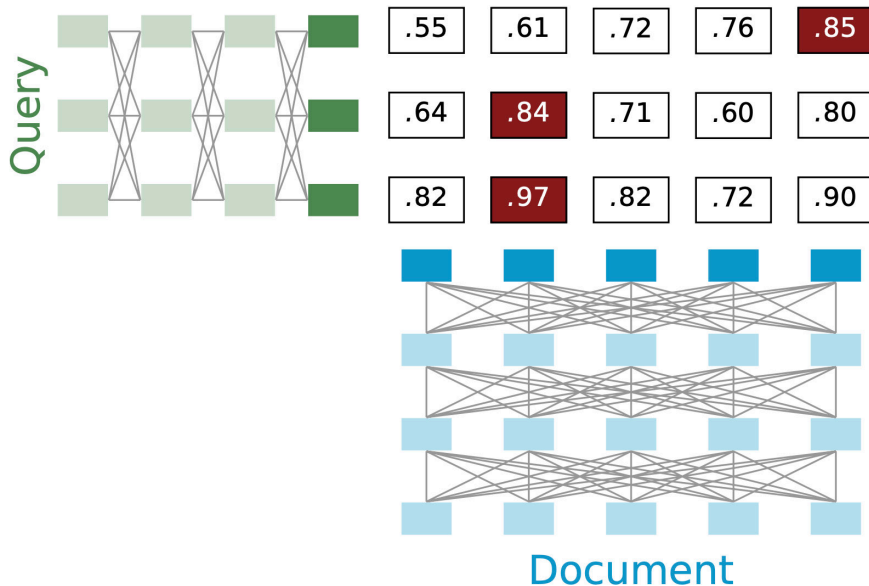


$$\text{MaxSim} = .97 + .84 + .85$$



Notice that ColBERT represents the document as a MATRIX, not a vector like the bi-encoder! $\mathbf{d}_i \in \mathbb{R}^{L \times d}$

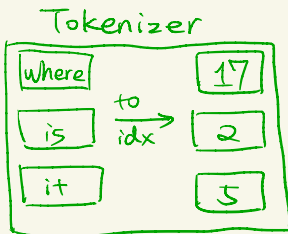
Query : where is it

Doc₁ : it is at the airport

To Embeddings

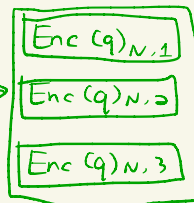
Query :

where is it



BERT

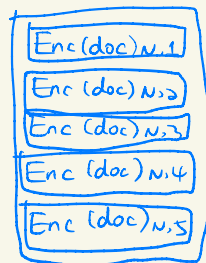
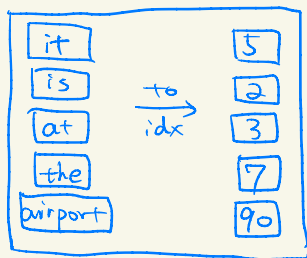
Last Layer(N)
of BERT



(Enc(q)_N)

Doc₁ :

it is at the airport



(Enc(doc)_N)

In PA3 ,

$$\text{Enc}(q)_{N,i} \in \mathbb{R}^{728}$$

$$\text{Enc}(\text{doc})_{N,i} \in \mathbb{R}^{728}$$



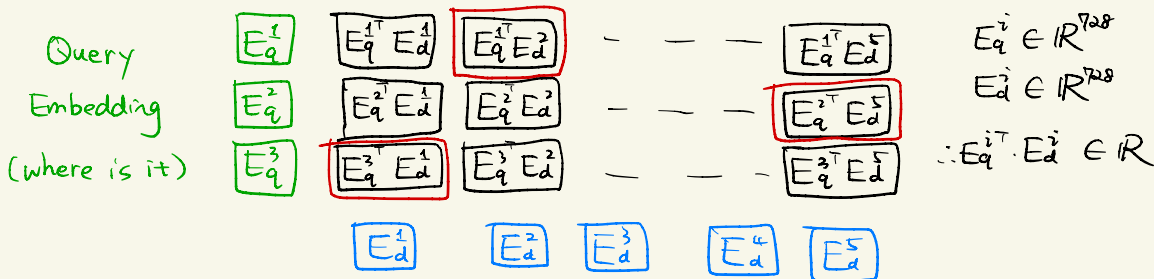
$$\text{Enc}(q)_N \in \mathbb{R}^{3 \times 728}$$

$$\text{Enc}(\text{doc})_N \in \mathbb{R}^{5 \times 728}$$

for this
example

CoBERT (Zero-shot Transfer Ver.)

For convenience, we denote $E_q^i := \text{Enc}(q)_{N,i}$, $E_d^i := \text{Enc}(doc)_{N,i}$
 (here we didn't apply L2 norm to the embeddings,
 but you are welcome to do so)



Doc 1 Embedding (it is at the airport)

Assume the scores being framed are the maximum across each row.
 Then the similarity for this (Query, Doc) pair will be

$$\begin{aligned} \text{MaxSim}(q, doc) &= \sum_i^L \max_j^M \text{Enc}(q)_{N,i}^T \text{Enc}(doc)_{N,j} = \sum_i^L \max_j^M E_q^{iT} \cdot E_d^j \\ &= E_q^{1T} \cdot E_d^2 + E_q^{2T} E_d^5 + E_q^{3T} \cdot E_d^1 \end{aligned}$$

where L is the length of q , M is the length of Doc .

Then calculate $\text{MaxSim}(q, \text{doc}_i)$ for each of the 15 docs retrieved, and get the top-5 docs.